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A Behavior Oriented Control System for Machining

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February 1991

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Table of Contents

List of Figures

ABSTRACT

This paper describes a new approach for controlling an intelligent machining workstation. The control system is built in behavior achieving layers, which allows a machine tool to operate at increasing levels of competence. Each layer focuses on a specific simple control task for machining processes. Qualitative reasoning is used to augment the system at the highest layer, giving the system the ability to foresee patterns of behavior that lead to failure. We discuss how qualitative models can be selected, setup and used to adjust control parameters.

1.0 INTRODUCTION

One focus of manufacturing research has been the development of integrated, self-adjusting manufacturing systems that are capable of machining varied parts without human supervision. Machining process automation has already been achieved for some routine operator functions such as the loading and unloading of work pieces and tools, parts scheduling and distributing, and initiating NC programs. The functions which remain to be developed include monitoring machining operations, ensuring safe and efficient metal removal rates, and taking corrective actions in the event of process disturbances or failures.

Traditional manufacturing control systems are based on a serial flow of information from sensors to actuators (see Figure 1.1). These control systems usually process one step at a time, which can make a machining system susceptible to unexpected events. In addition, a "serial controller" is plagued by a reliability bottleneck, i.e., every processing step has to work reliably in order for the whole system to advance to the next step [Bourne and Wright 1988].

As an alternative to a serial model of control, Brooks has proposed a parallel organization that is based on natural behavior [Brooks 1985]. This architecture controls complex amalgamations of simpler behaviors, and has lead to a tractable reformulation of the problem of combining multiple goals. We considered this control organization by translating Brooks' parallel mobile robot behaviors into parallel machine tool behaviors (see Figure 1.2).

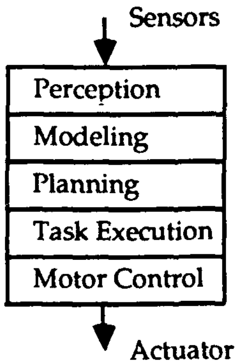


Figure 1.1: Traditional Flow of Information in a Control System [see Brooks 1985]

The architecture in Figure 1.2 was built up with a conservative view of preserving the machine first, the tools second and then various aspects of the part being produced.

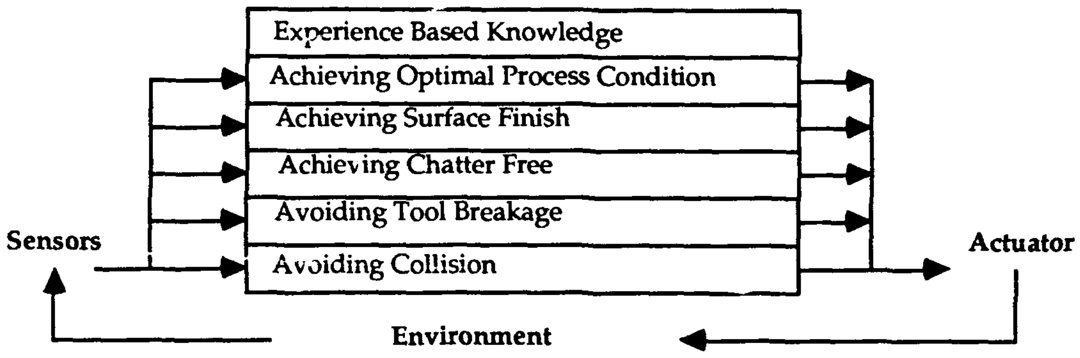


Figure 1.2: A Parallel Architecture [modified from Wright and Bourne 1988]

Avoiding Machine Damage:
Machine damage is a serious consequence. The Avoid Machine Damage behavior can be decomposed into its subbehaviors which focus on simpler task achieving behaviors. The implementation of these subbehaviors involves predicting possible machine faults and protecting the machine tool from various events. To avoid conflicts with other behaviors, behaviors that protect equipment, tools or parts should have a high priority in order to respond emergency situations in the machining process.

Avoiding Part Damage:
A damaged work piece can be caused by a worn tool or the processing state of the machine tool. To achieve the goal of avoiding part damage, the control system must maintain the following device behaviors:

- Achieving an optimal process condition: Optimal cutting conditions improve surface finish and reduce the risk of tool breakage.

- Achieving a chatter free condition: Maintaining a chatter free condition protects the surface finish, the part geometry, the tools, fixtures and even the machine itself.

- Avoiding tool breakage: A broken tool almost guarantees that the part has to be scrapped. In addition, it also poses other dangers to the environment, such as a tool piece spinning free from the machine, threatening human observers.

Achieving Part Geometry:
The machining control system must be able to achieve the desired part geometry defined by the technical design. The planning process decomposes the whole machining task into a well-defined sequence of cutting features (e.g., a hole, a slot, a chamfer, etc.). Online measurement and compensation behaviors for the changes of tool size and offset between tool and parts are essential for the goal of Achieving Part Geometry [Smith 1989].

1.1 Machining Situations
To test the ideas in this paper, we offer a few machining situations that have proven to be very difficult to automatically control. We believe that the methods in this paper will begin to make these problems and others like them more manageable.

Situation 1: A slot is being milled into a part. However, chips begin to become irregular and broken with uneven serrations and a large collar forms along the slot. As a result, the machinist believes that there is increasing flank wear and that the tool may break at any moment.

Situation 2: The rough cutting of a part's surface is normal and the tool has only slight flank wear. The chip forming appears repetitive with a constant radius of chip curvature. It seems that current cutting condition is good, but the machinist notices that the surface finish is much worse than expected.

Situation 3: A new tool is working smoothly. Suddenly, serious chatter begins that causes a dull surface and a higher interface temperature between tool and part.

In the machining process, unexpected events can result in machine tool or work piece damage. Tool breakage, collision, chatter and other machine behaviors are best predicted ahead of time. In our approach, the control system watches for early signs of these key events.

1.2 Previous Research Work

Since 1985, our research has focused on intelligent manufacturing systems. We have investigated the interactions between complex modules used in manufacturing, e.g., a planning expert, a cutting expert, a modeling system, a sensing expert and a holding expert. With these systems, we built the Intelligent Machining Workstation (IMW) to automate the production of single, 3D, mechanical parts [Bourne 1987,1983; Hayes 1987]. We also performed several experiments to test the usefulness of qualitative reasoning in machining control, and proposed how to use appropriate control regimes for a given task [Bourne and Wright 1988]. We now combine these ideas with the Brooks model [Brooks 1985] of behavioral control.

2.0 A BEHAVIOR ORIENTED CONTROL SYSTEM FOR MACHINING

2.1 Building The System

One useful system has five control layers. Each layer senses the machining environment according to its own control task and implements its own control solution. Generally, the lower layers have a higher priority and a shorter response time in order to protect both the machine tool and work pieces. The control commands are executed by actuators that change rotation speed, feed rate and cutting depth or they can perform an emergency stop. The priority mechanism is controlled explicitly by allowing the lower layers to *inhibit* the output of the higher layers (notated "I" in Figure 2.1). In practice, the control system in Figure 2.1 would almost certainly have more intricate connections between the layers.

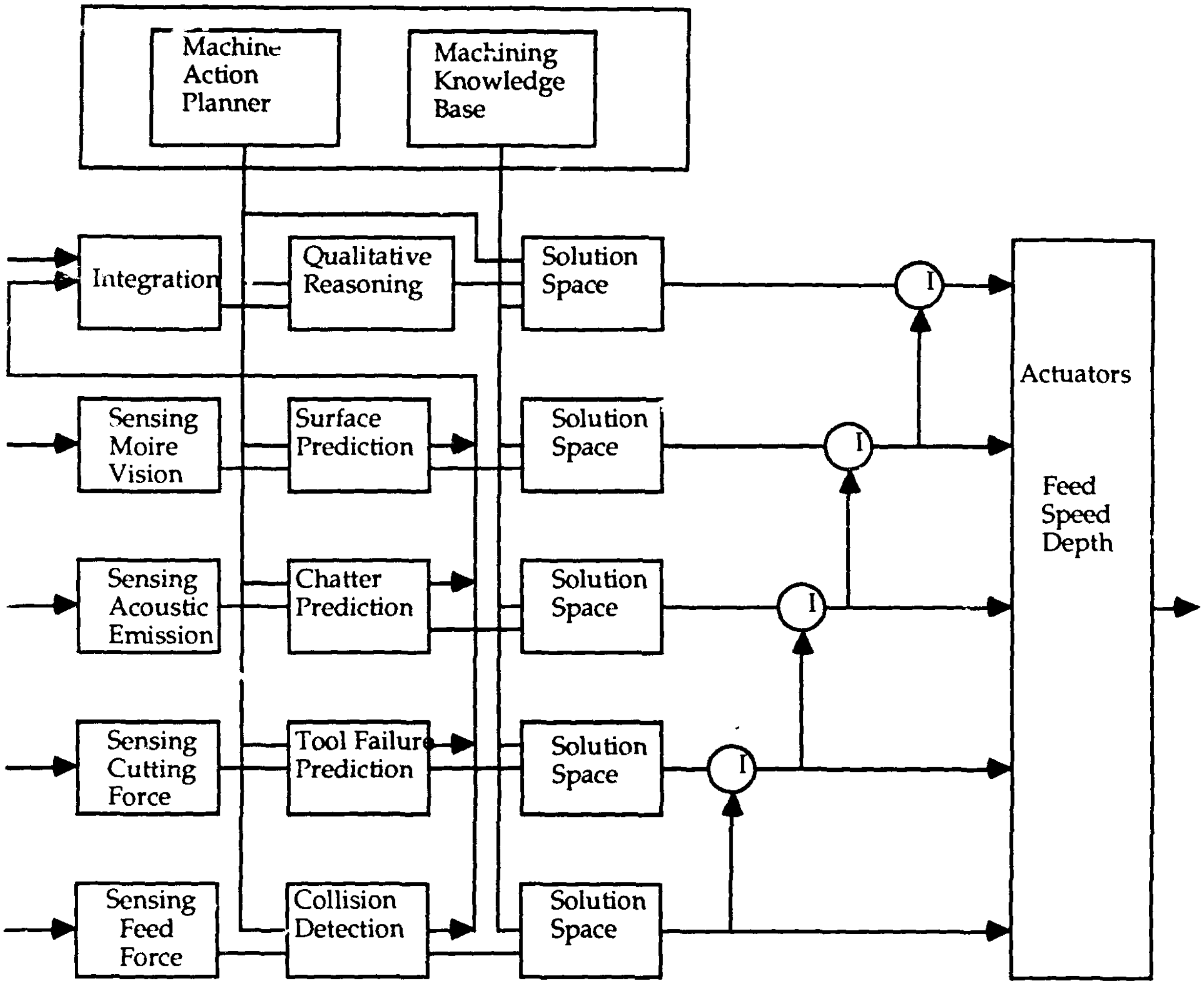


Figure 2.1: A Multiple Layer Model for Machining Control

2.2.1 Structure of The System

The First Layer: Avoiding Collisions

The first layer avoids collisions by using computed geometric information from the fifth layer to protect the machine tool from damage. By sensing the machining force signals (e.g., machine power consumption) in different machining phases, this control layer can send HALT commands to actuators in case an accidental collision occurs [Balakrishnan and MacBain 1985; Smith 1989]. Collision detection requires very short response times and almost impossible to stop the machine motors in time to avoid damage, so it is critical to avoid the collisions in the first place.

The Second Layer: Avoiding Tool Breakage

The second layer avoids tool breakage by sensing cutting forces, by monitoring tool failure and predicting tool breakage [Ramamurthi and Shaver 1990; Smith 1989]. The result of monitoring forces provides necessary variables for qualitative reasoning in the fifth layer. Combining the prediction of process behaviors from the fifth level and the

real time prediction on this level, the second level can usually stop cutting before tool breakage.

The Third Layer: Avoiding Chatter

The third layer focuses on predicting chatter and trying to avoid work piece and tool damage [Smith 1989; Sturges 1989]. The control strategies are executed online to achieve a chatter free condition when chatter is not serious. If serious chatter does happen, the layer will first stop the feed and spindle rotation, and then it will implement an offline strategy to achieve a chatter free condition. This involves changing the tooling and/or refixturing the part.

The Fourth Layer: Achieving Geometry and Surface Finish

The fourth layer system implements control strategies for achieving satisfactory surface quality. As input to this layer, the current surface finish is sensed through one of several methods: acoustic emissions [Sturges 1989], ultrasonics [Eitzen 1990] or Moire vision [Bieringer et al 1988].

During a rough cutting process, a high metal removal rate is more important than the resulting surface finish. The surface finish as a performance index of cutting process is considered on the fifth layer together with other indices to optimize machine utilization. During finish cutting, the surface finish is more important than the metal removal rate. The fourth control layer takes control of the fine cutting stage with special control strategies (decreased cutting depth with slower feedrates and increased spindle speed).

The Fifth Layer: Predicting The Unexpected

The fifth layer implements predictive control based on machining expertise. The process parameters which describe the important features of machining process are monitored first in the lower layers and this layer integrates these quantitative values into meaningful symbols.

Qualitative simulation with integrated process model and current process states are used to generate possible upcoming behaviors [Forbus 1985; Kuipers 1989]. From these results the planner searches for early signs of problems, and what variables should be adjusted to steer the machine into behaviors that are consistently safe and productive. Finally, this information is sent to the lower layers in order to guide their decision making.

Figure 2-2 shows one result from a simple qualitative model. In this example, the parameters: surface finish undulation, tool flank wear, chip size, and collar size (i.e., material pushed up at the rim of the cut) are used to describe the current state of the machining process. As the various values approach dangerous levels, the machine attempts to adjust parameters that will lead away from danger.

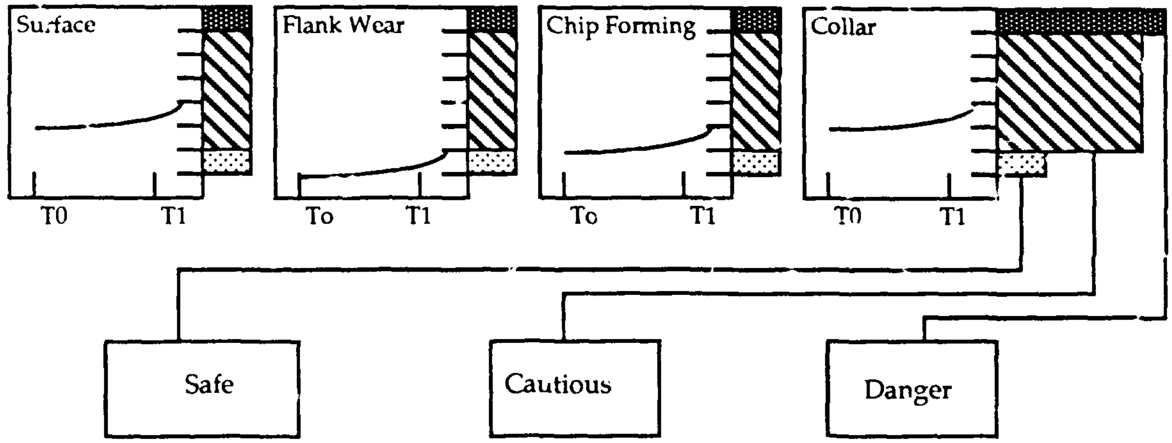


Figure 2.2: Qualitative Reasoning about Cutting Process

By analyzing each behavioral pattern with knowledge from human machining experts, eliminating some patterns which violate physical constraints among process variables, a behavioral space can be built up. According to the physical characteristics of every behavioral pattern, it is possible to recognize a safe behavioral zone, a dangerous behavioral zone and a cautious behavioral zone for which the control variables must be adjusted for achieving all the goals of the machining process (see Figure 2.2).

Qualitative reasoning can predict the possible behaviors of an incompletely described system [Kuipers 1989; Forbus 1985]. Wright and Bourne [1988] described a qualitative control system for manufacturing, Kuipers and Dvorak [1989] also implemented a qualitative process monitoring system, which highlights the design philosophy for this control level.

3.0 Qualitative Simulation in Machining

We have employed qualitative simulation using QSIM [Kuipers 1985] to model processes, to predict behavior, and to describe behavior. To perform these tasks in machining, the models have to cover a wide range of topics. We have identified seven qualitative models that should be built:

(1) Tool Wear (a qualitative version of a physical model)
(2) Cutting (a qualitative version of a physical model)
(3) Sensing (a qualitative version of a physical model)
(4) Fixturing (a qualitative version of a physical model)
(5) Chip Formation
(6) Mediation in Distributed Problem Solving
(7) Strategy Selection (i.e., How conservative should the approach be?)

We have developed rudimentary models for tool wear, cutting and fixturing. Future work will refine these three models and provide models that cover the other topics. The

models tend to partially overlap and so the system as a whole has a rule-based understanding of what issues are being solved at any given time. For example, behaviors of surface finish in different time intervals describe both surface quality, which is an important quality index, and a tool wear state, which is a key parameter for machining.

Figure 2.2 is a behavioral description that results from reasoning about machining in two time intervals. It shows that the state of the machining is good and that the process will be working smoothly between T0 to T1. It also shows that the state of machining is deteriorating between T1 to T2. The value of each parameter is represented by an ordered pair:

[landmark, direction]

where the landmarks are a meaningful ordered-set of symbolic values for the parameter and the direction expresses the time varying tendency of the value (increasing, decreasing or steady).

A behavioral space is a matrix (see Figure 3.1) that represents all the possible behavior patterns in the machining process, which is any legal assignment of values to each parameter in the model. In a behavioral space, every behavioral pattern represents a possible process state, which reflects some physical phenomena in machining. Predicting process behaviors can result from qualitative reasoning by starting with actual values measured from machining, and then matching the prediction to the behavioral space. Finally, the trends represented by the current behavioral pattern as well as subsequent behaviors can be used to adjust key control parameters.

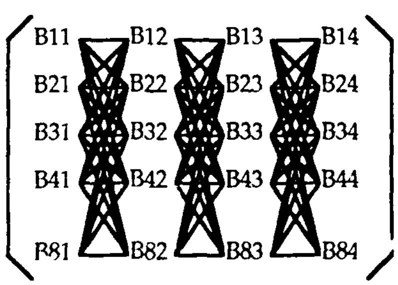
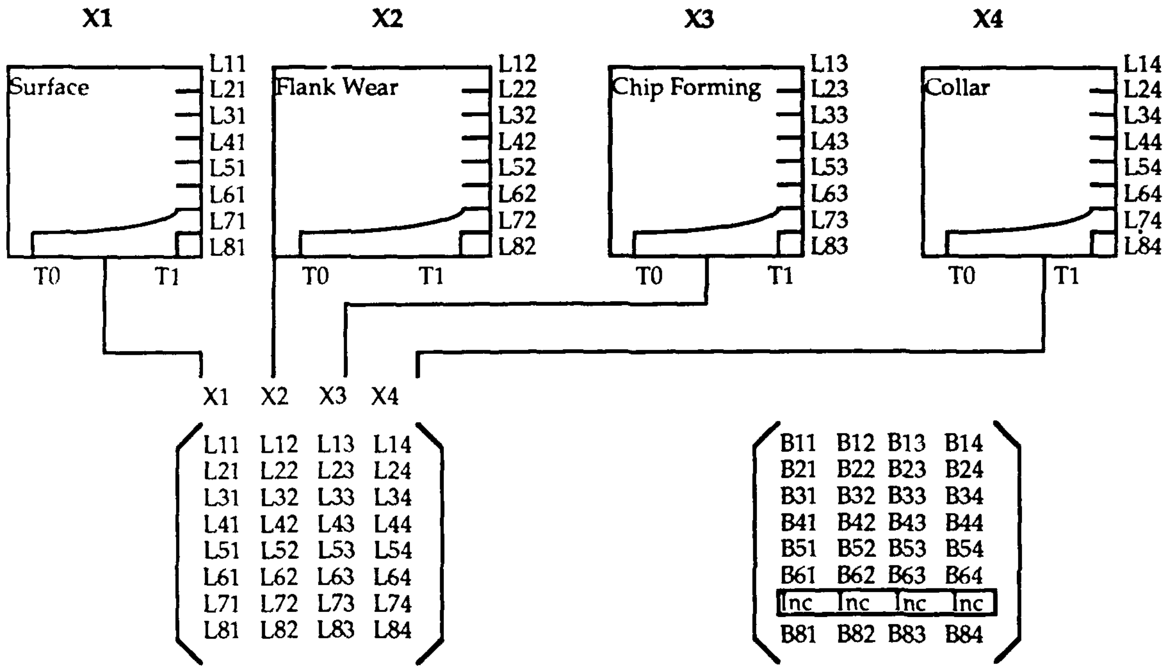


Figure 3.1: Behavioral Pattern Space of Process



a. All possible values for every parameter in the behavioral space.

b. Behaviors from each parameter form a behavioral pattern, which describes a possible behavior in the machining process.

Behavior={ (B71=Inc.), (B72=Inc.), (B73=Inc.), (B74=Inc.)}

in which

B71 is a behavior of the first parameter, surface finish, which is an increasing value from landmark Smooth towards landmark Dull.
B72 is a behavior of the second parameter, tool wear, which is an increasing value from landmark Running-in towards landmark Steady.
B73 is a behavior of the third parameter, chip forming, which is an increasing value from landmark Even towards landmark Uneven.
B74 is a behavior of the fourth parameter, collar, which is a still increasing value from landmark None towards Inchoate.

Figure 3.2: Generating the Behavior Space

The four values of the process parameters form a behavior pattern and describe a physical state of the machining process as: the tool is basically new, the surface finish is not bad, the chip and collar is normal, the state of machining is good and it is not necessary to adjust process control variables.

As a sample, a model was derived from Paul Wright's knowledge engineering experiments [1988] on tool wear (see Figure 3.3). One conclusion drawn from these experiments was that the machinist divides tool wear into three stages: (a) *running-in*

wear; (b) *steady* state wear; and (c) *rapid,* fatal wear. To differentiate the three stages, the machinist employs visual, aural, and tactile clues. Figure 3.3 is a listing of the model as it was input into QSIM in order to perform a qualitative simulation. Qualitative models have three main elements:

- **Quantity-Spaces** is a list of the parameters that pertain to the model. Also, associated with each parameter is a list of the possible values for that parameter. The parameter values are to be viewed as ordinal values. For example, the values associated with the parameter *collar-formation* signify the amount of collar that has formed ahead of the cutting tool. We have *none* equaling no collar formation, *inchoate* meaning that the collar has just begun to form, and *large* signifying large collar formation.

- **Constraints** is a list of constraints that defines how the parameters interact. The constraint "((~DEC flank-wear))", for example, states that the value of the parameter *flank-wear* may never decrease. That is, if *flank-wear* is equal to *steady* it may never again be equal to *running-in*. The constraint "((D/DT db db-fluctuation))", says that *db-fluctuation* is the rate of change of *db*. The "M+" constraints are slightly more complicated. As an example, the semantics of the constraint, "((M+ surface-finish flank-wear) (smooth running-in) (dull steady) (unacceptable rapid))" declare that *surface-finish* is positively correlated with *flank-wear*. The lists, "(smooth running-in)", "(dull steady)", and "(unacceptable rapid)" are referred to as corresponding values and state that when *surface-finish* is equal to *smooth, flank-wear* is equal to *running-in;* when *surface-finish* is equal to *dull, flank-wear* is equal to *steady;* and so on.

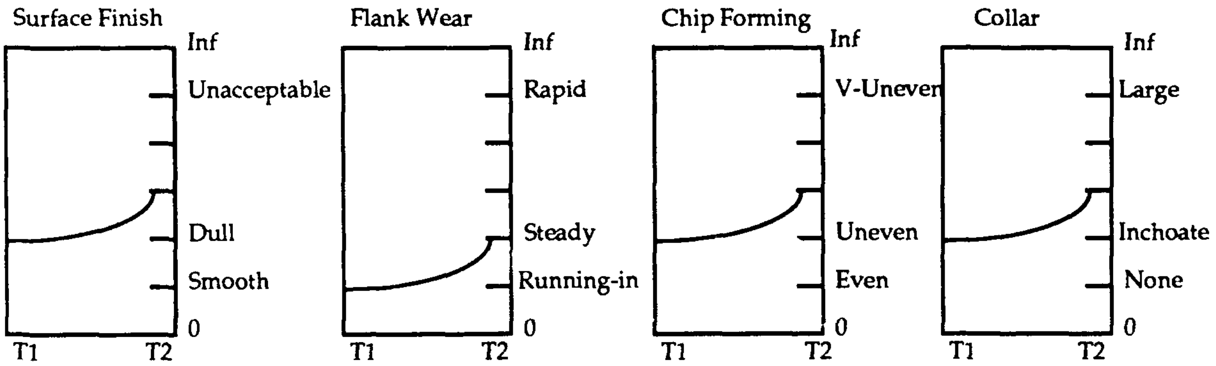
- **Dependent** is a list of parameters that can fluctuate in the simulation process. The constraints determine the legal fluctuations.

The choice of parameters in the models is critical. Some of them are easily observable and should be almost always included, if they can be related to important control parameters. Some of the parameters are inherently unobservable, but are quite significant in explaining the fundamentals of the situation. These variables should also be included, when they can be partially guessed from other more easily observable parameters. If there is no connection with observable parameters, then it is pointless to even mention these parameters. Perhaps, the most important parameters are the ones that can be adjusted, since the strategy for qualitative control is to predict "safe" regions of operations and to use the adjustable parameters to stay within these bounds.

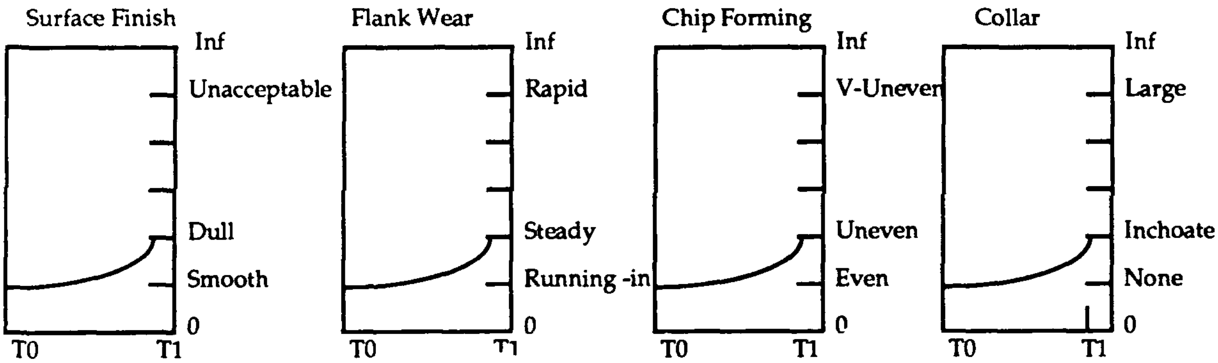
```
;*   Notation: Keywords recognized by QSIM are in capitals and comments are
;*   preceded by ";*".

(DEFINE-QDE toolwear ;*Define a qualitative equation by the name of "toolwear"

(QUANTITY-SPACE ;*  Parameters and their possible values
      (chip (even uneven  very-uneven  inf))               ;* Chip Type
      (collar-formation (none  inchoate  large  inf))      ;* Part Anomoly
      (flank-wear (running-in  steady  rapid  inf))        ;* Tool Wear
      (surface-finish (smooth  dull  unacceptable  inf))   ;* Part Smoothness
      (db (0  background  machining  inf))                 ;* Acoustic Signal
      (db-fluctuation (0 very-little  some  wildly  inf))  ;* Changes in
      (trickle (even  uneven  very-uneven  inf)) )         ;*

(CONSTRAINTS ;*  Manner in which parameters may interact
    ( (~DEC flank-wear) )
    ( (D/DT db db-fluctuation) )
    ( (M+ chip flank-wear)
      (even  running-in)
      (uneven  steady)
      (very-uneven  rapid) )

    ( (M+ collar-formation flank-wear)
      (none  running-in)
      (inchoate  steady)
      (large  rapid) )

    ( (M+ surface-finish flank-wear)
      (smooth  running-in)
      (dull  steady)
      (unacceptable  rapid) )

    ( (M+ db-fluctuation flank-wear)
      (very-little  running-in)
      (some  steady)
      (wildly  rapid) )

    ( (M+ trickle flank-wear)
      (even  running-in)
      (uneven  steady)
      (very-uneven  rapid) ))

    (DEPENDENT chip  collar-formation  db  db-fluctuation flank-wear
         surface-finish  trickle))
```

Figure 3.3: Tool Wear Model Segment

Figure 3.4 illustrates some results from running the model in Figure 3.3. One weakness of this example is that there are not control variables that are easy to manipulate. As a result, the decisions have to be inferred by a rule.



The behaviors from four process parameters make up of a specific behavioral pattern. According to this pattern, the deterioration of a machining process occurs from T1 to T2.



Another behavioral pattern of the machining process works smoothly from T0 to T1.

Figure 3.4: Qualitative Reasoning with Integrated Process Parameters

3.1 Selecting and Running Qualitative Models

Having a set of models that describe a complex process like machining is only the first step of making them useful. Perhaps more difficult than making the model in the first place is setting the model up with appropriate initial values so that it can generate a behavior space suitable for the current situation.

In order to select and suitably execute a QSIM model, we have interfaced it to a rule-based system (OPS5). In the rule system, we have described when a particular model is useful and how it can be setup for the current machining situation. Figure 3.5 outlines the rather elaborate approach to select a simulation model and then acquiring values that will allow it to run and provide useful information.

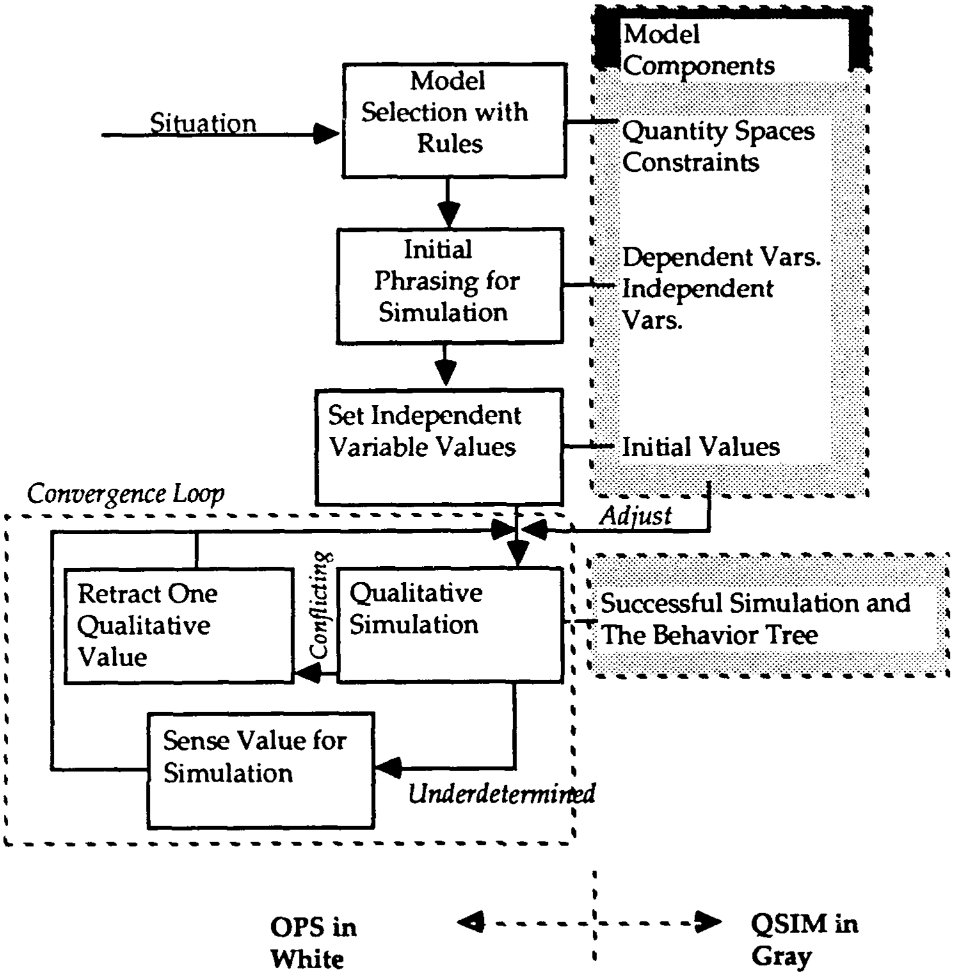


Figure 3.5: Algorithm for Automatic Model Selection and Setup

Three of the boxes in Figure 3.5 (*Model Selection with Rules, Initial Phrasing for Simulation,* and *Set Independent Variable Values*) automatically build a model to be simulated. The initialization of a model is strongly influenced by the purpose of the simulation; that is, whether it is for prediction, diagnosis or mediation. The *Convergence Loop* manages the two causes for failing to complete a new simulation state: (1) underdetermined parameter values and (2) conflicting parameter values.

When a request is received by lower layers of the controller, and a qualitative simulation of a model needs to be performed, there is no guarantee that values will be available for all of the model's parameters. However, this gives the lower layers of the controller a clear objective: obtain from sensing the values necessary to run the model.

One of the features of QSIM is the existence of rules that assign values to parameters that have no current values. So even though a model has underdetermined parameters, an attempt to make a valid simulation may go forward. Even with this feature, the simulation may fail. A failure in this circumstances is known as "underdetermined" and

is to be handled by *Sense Value for Simulation*. This involves querying the rest of the controller for a possible initial value for the parameter. If *Sense Value for Simulation* gets one of the underdetermined parameters, QSIM may be able to determine the rest. However, even then the system should confirm these values, if possible.

Conflicting values are an other cause of *simulation failure*, which is not the result of underdetermined parameters, but rather parameters whose values are deemed to conflict according to the constraints. The easiest explanation is via an example. Take the following two constraints [slightly modified from our toolwear model]:

(a) ((M+ collar-formation flank-wear) (none running-in) (small steady))
(b) ((M+ surface-finish flank-wear) (smooth running-in) (dull steady))

The first clause of both expressions describes the listed parameters (e.g., collar-formation and flank-wear) as positively increasing and correlated. The second and third clause in both expressions list values that must simultaneously correspond. In the initial state, the parameters could have the following values:

collar-formation=none
surface-finish=dull

In this situation, the system was unable to assign a value to *flank-wear* that did not cause a conflict between two constraints. That is, *collar-formation* equal to *none* dictates that *flank-wear* be assigned the value *running-in*, and *surface-finish* equal to *dull* constrains the value of *flank-wear* to *steady*. *Flank-wear* cannot be equal to *running-in* and *steady* at the same time. A simulation failure due to conflicting parameter values is handled by the box labeled *Retract One Qualitative Value*. It must determine which of the parameters is invalid or it must consider the fact that the model may not be complete.

QSIM has been modified to provide information about underdetermined and conflicting values when an error in simulation is encountered.

3.2 Using The Results of Qualitative Simulation in Behavioral Control

The result of qualitative simulation is a behavior space that corresponds to the constraints of the model. To make effective use out of this behavior space, we must search for favorable behaviors and then adjust machine parameters to steer the process into those behaviors, while avoiding the less favorable outcomes.

3.3 Behavioral Control and Machining Situations

The three machining situations introduced earlier in the paper are now reconsidered with this machining architecture: a series of behavior achieving control layers and a qualitative approach to predict machine behaviors before they occur.

Situation 1: A chip model can be built to relate the shape, size and evenness of a chip to tool wear. However, it is quite difficult to sense the quality of the chips inprocess. Therefore, the system would probably have to rely on rapidly increasing cutting forces and the existence of chatter to make the prediction. These conditions are mostly handled by the real time layers of the control system and do not require advanced prediction beyond this. However, the qualitative simulation could provide an explanation for an action in a later diagnosis phase.

Situation 2: This situation describes a normal machining state. However, since it has been recognized that the surface finish is not measuring up to the specification, it is necessary to adjust the key process parameters. The models required to accomplish this must describe the basic cutting process. For example, a high feedrate is often accompanied with some tool deflection that can adversely affect the surface finish. In addition, the rotational speed of the tool can be under increased load from taking too deep a cut. Therefore, these simple relationships can determine that the feedrate should be decreased and possibly that the speed should be increased.

Situation 3: Again this situation can rely on the built in control layers, which suggests that the qualitative reasoning comes into play when unobservables play dominate roles in the machining process.

4.0 DISCUSSION

4.1 Behavioral Control

We have proposed combining two diverse methods to achieve a sound method of control for machining (and other manufacturing processes): building a behavior oriented structure coupled with a high level method (Qualitative Simulation) of predicting upcoming behaviors. Controllers that are sold in the marketplace inevitably implement some aspects of behavioral control with an awkward mix of hardware and special purpose low-level software. However, this approach is only implemented at very low levels (e.g., machine stalls) and it is not followed through as successively more sophisticated layers are added. We believe that by systematically applying this approach that there will be many spinoff benefits:

- **Robustness** - If one layer in the system fails, there is a backup response.
- **Flexibility** - Related to robustness, the system can adapt to the environment by sensing the actual situation and pursuing a behavior that is both safe and productive.
- **Appropriate Speed** - The behaviors are ordered by their required response time so that situations can be handled ontime.
- **Quality** - The quality of the part production is factored into the behavior of the system so that the part can be produced within specification, so long as it is possible for the machine to do it safely.

4.2 Prediction with Qualitative Simulation

Within a behavior oriented control system, it is necessary to have a module that "thinks ahead." We believe that there are some elements of qualitative simulation that are promising in this area:

- **Explicitly Represented Physical Process** - Some understanding of the physical processes is built into the control, so that it can use results from scientific study as a crystal ball.

- **Enumerated Behaviors** - Built into the idea of qualitative simulation is the idea that all possible behaviors, within the constraints of the equations, will be enumerated. This is both qualitative simulations greatest strength and weakness. Designers can miss a behavior in their design, which can result in a machine crash. On the other hand, enumerating all of the possible behaviors can be time consuming and once they are generated, it can be difficult to navigate to truly useful (or likely) behaviors.

There is much more work to be done on predicting the likely behavior of a manufacturing process, but we believe that by combining a fundamental approach to prediction, with a behavior oriented control system can achieve the desired manufacturing objectives.

5.0 ACKNOWLEDGEMENTS

We would like to thank Ben Kuipers at the University of Texas for making his software QSIM for qualitative reasoning available to us. This esprit de corps has allowed us to build on his work and apply his results to new domains. This work is also partially inspired by our fellow colleagues: Paul Wright, Paul Erion, Caroline Hayes and Brack Hazen. We would also like to thank the U.S. Air Force, the Materials Lab at Wright Patterson, for partially supporting this work.

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